Surrounding Vehicles' Lane Change Maneuver Prediction and Detection for Intelligent Vehicles: A Comprehensive Review

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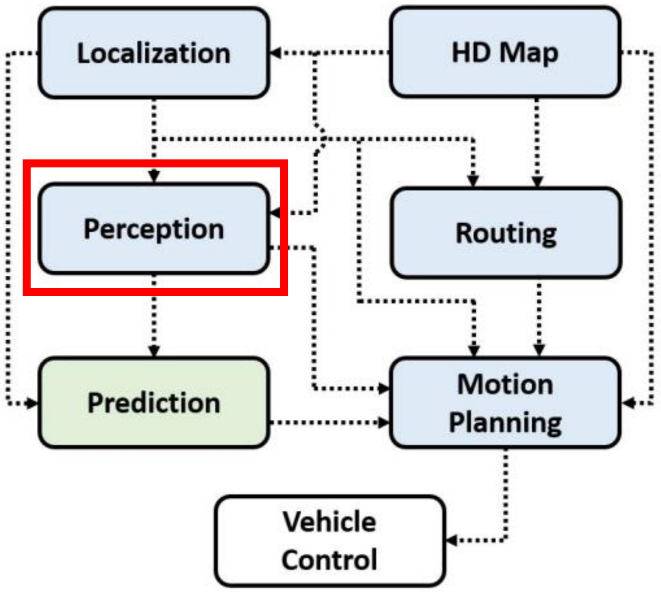
1. Introduction

Human error is involved in 94 to 96 percent of all motor vehicle crashes

Autonomous Driving Technology



Perception detect

1. Surrounding environment
2. Pedestrians
3. Vehicles
4. Traffic lights
5. Traffic signs

→ Avoid accidents

1. Introduction

<Ego vehicle>

Static objects

- Not change position

Moving objects

- Changing position
- Uncertainty of their future position

→ Affects safety of the Autonomous Vehicle

- Prevent collisions
  - Identify object’s location at current time
  - Predict object’s future position

Lane Change

Good predictions of Surrounding vehicles’ lane change maneuvers

- Improve intelligent vehicles’ safety
- Improve passengers’ comfort

1. Introduction

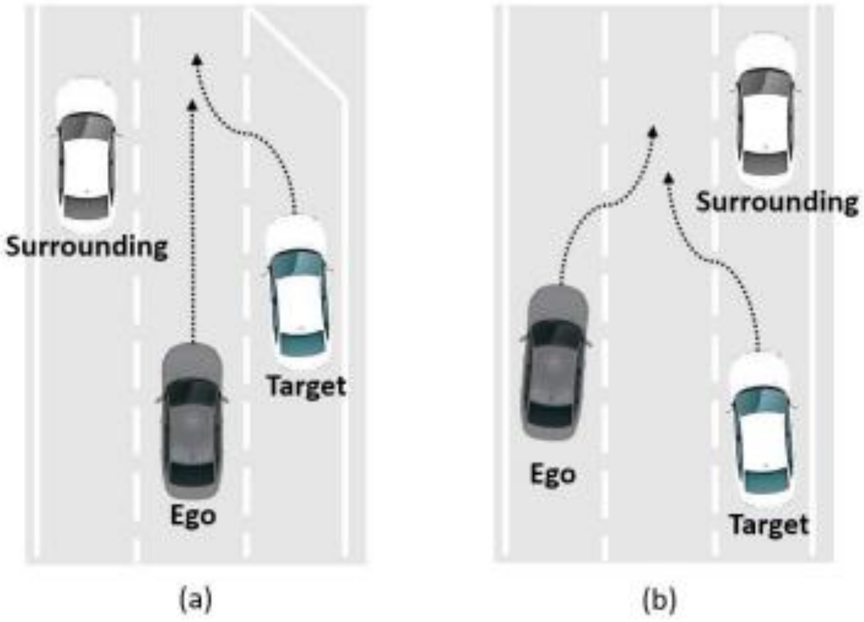
Aims to give readers overview of the state-of-the-art research

on the surrounding vehicles' lane change inference for intelligent vehicles

1) Introduce lane change maneuver basic concept

2) Prospects of prediction and detection of surrounding vehicles' lane change

2. Basic Concepts and Problem Formulation



ACC
(Adaptive Cruise Control)

(a)
- Another vehicle tries to cut-in in front of the intelligent vehicle

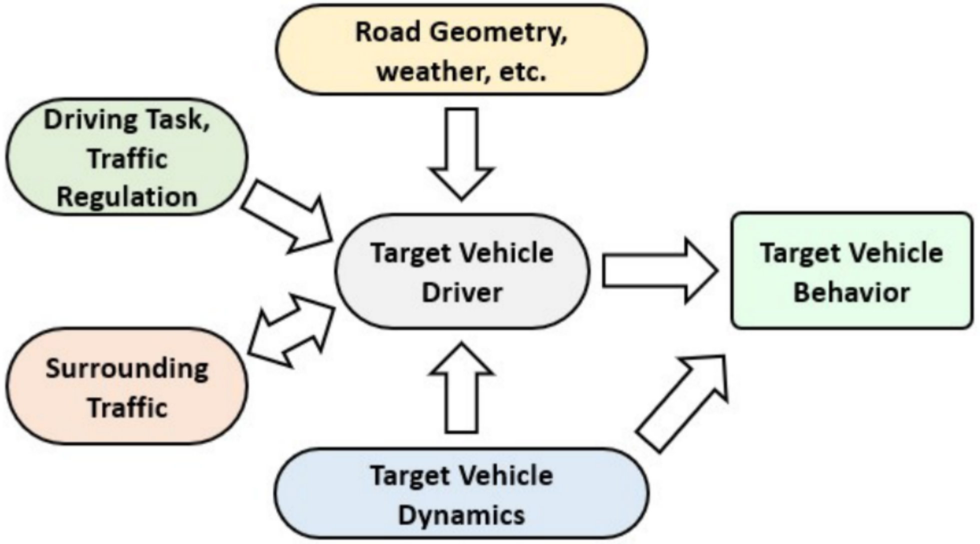
- ACC fails to detect lane change or cut-in situation
  ↪ Intelligent vehicle is likely to crash on the cut-in vehicle

(b)
- Other vehicles are going to change their lanes
  Move same range in the target lane intelligent vehicle

- Autonomous driving system
  ↪ Immediately abort the lane change
  ↪ Perform other evasive maneuvers

➡ Timely recognition can facilitate early and smooth reactions of the system and reduce hand-over

2. Basic Concepts and Problem Formulation



Target vehicle behavior
=
Driver's control + Vehicle dynamics

Driver's lane change intention ≒ Predicting target vehicle's lane change maneuver

Lane change intention affected the surrounding traffic, road geometry,
traffic regulations, driver's destination, etc

Ego vehicle predict

1. Driver intention
2. Lane change maneuver

Predicted lane change maneuver happening reasonable period of time in the future

⬇

5 ~ 10 seconds

Too long time

- Downstream controller can hardly determine when to react to the possible lane change

↪ Prediction result become hard to use

Time duration long enough

- Prediction model can calculate accurately when the lane change will happen

↪ Almost always better to prediction as early as possible

2. Basic Concepts and Problem Formulation (Driver Behavior)

Unintended

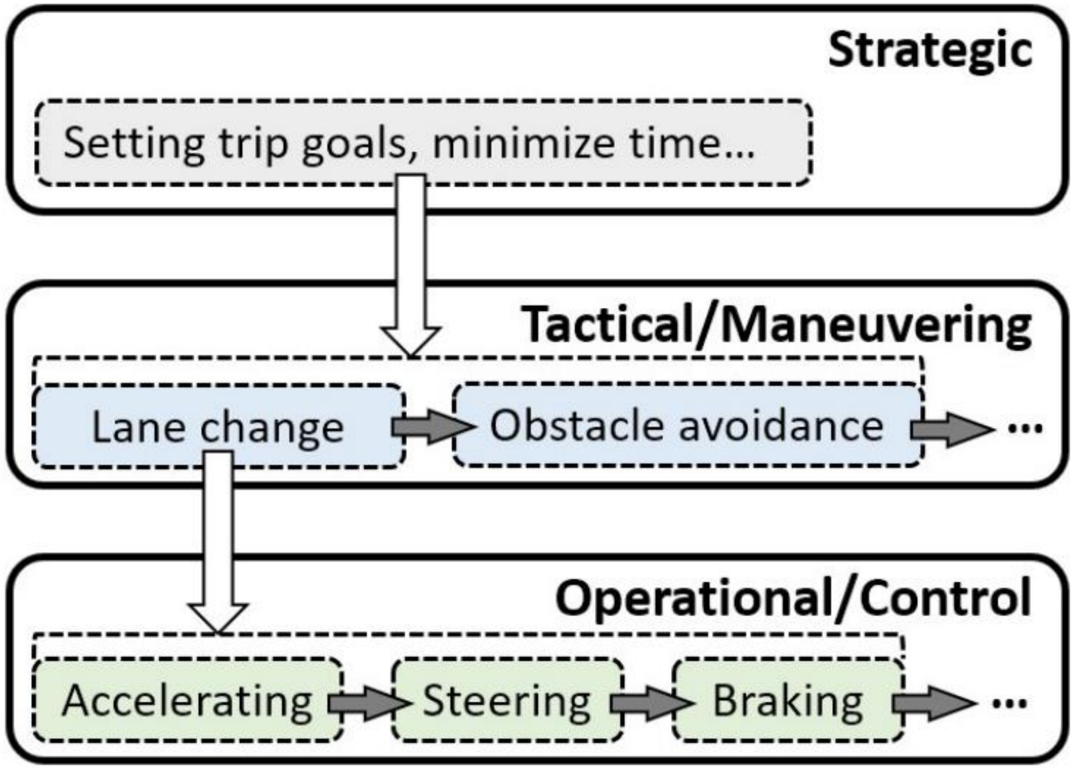
- Distractions and Workload
- Multi-tasking
- Fatigue

→ Difficult to predict

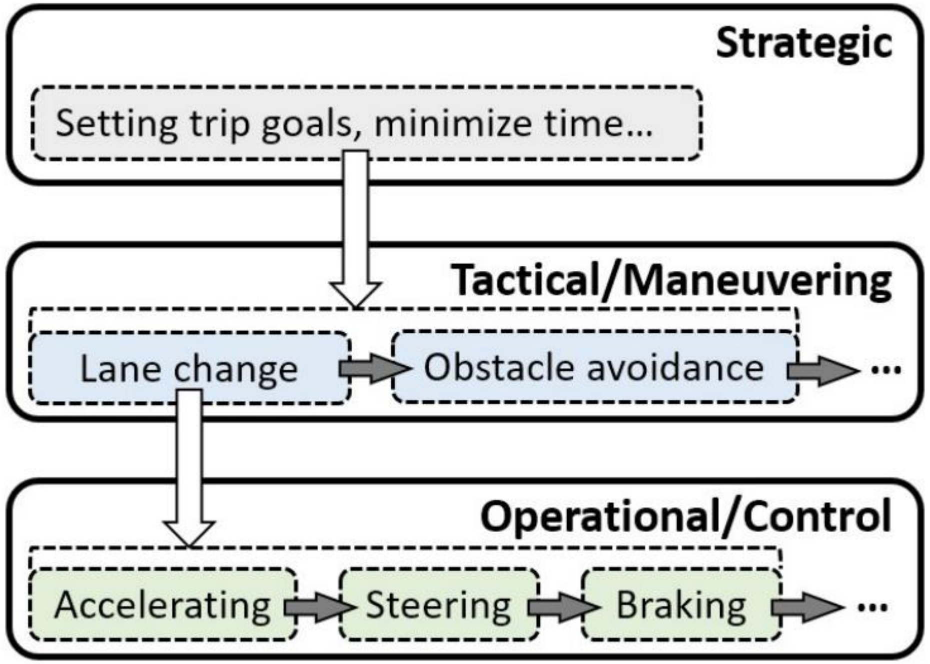
→ Model relies on vehicle's behavior to 'detect' rather than to 'predict' the lane change

Intended

- Most of the lane change maneuver belong
- Strategic
- Tactical / Maneuvering
- Operational / Control

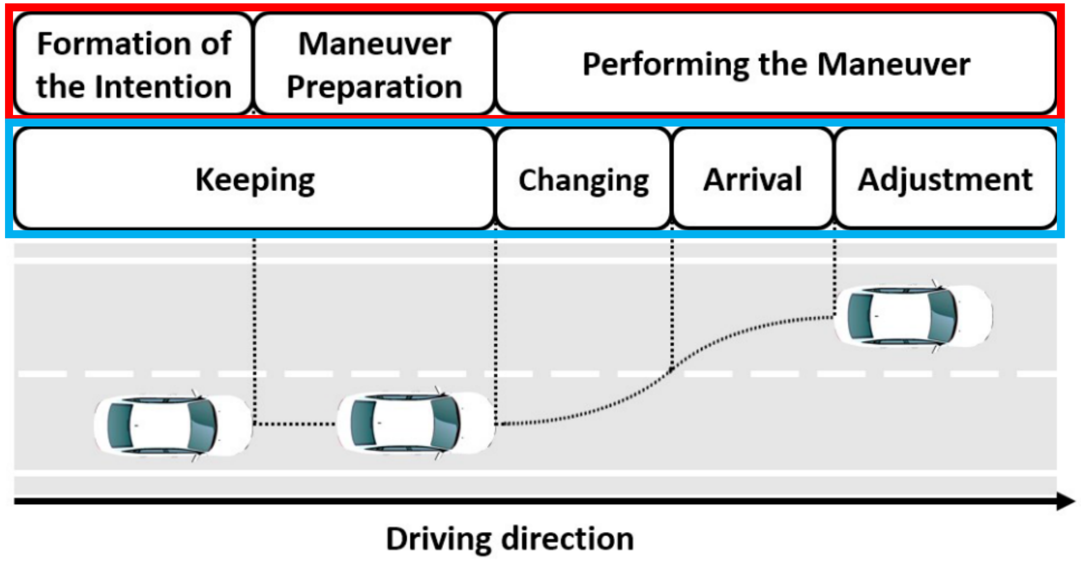


2. Basic Concepts and Problem Formulation (Driver Behavior)



- Lower level decisions are aligned higher-level decisions
- Strategic level, as the highest concept, influences the tactical and operational levels of driving
- Strategic decisions enable prediction of lane change likelihood and timing
- Detecting operational driving behaviors reveals if a vehicle is changing lanes

2. Basic Concepts and Problem Formulation (Lane Change Modelling)



→ 3 phase (Driver's intention)

→ 4 phase (Behavior of the vehicle)

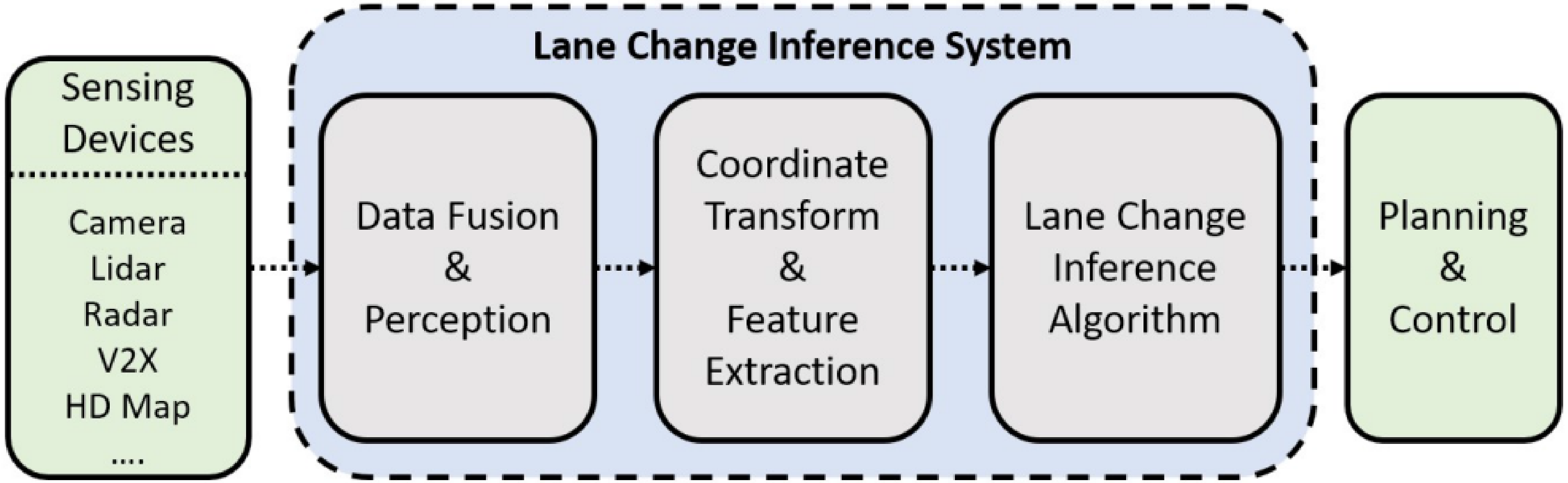
Lane change maneuver is divided into sub-phases according to the driver's intention

Formation of the Intention
- Drivers assess their surroundings and intend to move to a better lane if available

Maneuver Preparation
- Driver will double-check the surrounding environment to ensure safety

Performing the Maneuver
- When driver initiates lane change, it leads to changes in the vehicle's status and movement

3. Lane Change Maneuver Inference



1. Data Fusion

Combines signals from sensors to gather environmental and traffic data

2. Coordinate Conversion

Translates data from the ego vehicle’s system to the target vehicle’s system

3. Processing

Converts data into features for the inference algorithm

4. Inference Output

Algorithm analyzes these features to infer lane changes and informs downstream modules

3. Lane Change Maneuver Inference (Inputs for Lane Change Maneuver Inference)

Input : Environment context, Status of the vehicle, Driver behavior

1) Environment context

- Dynamic environment
  - Moving neighboring traffic
  - pedestrians, vehicles
- Static environment
  - Road / terrain information
  - traffic signs, weather condition

Environment information is only available on vehicles equipped with sensors for the higher-level autonomous driving system

Inference systems using this information usually can detect the lane change maneuver early

3. Lane Change Maneuver Inference (Inputs for Lane Change Maneuver Inference)

1) Environment context

(1)

- Predict the lane change maneuver
- Used four neighboring vehicles'
- Longitudinal relative speed
- Distance between neighboring vehicles'

(2)

- Considered the weather information
- Significant differences were observed
- Most parameters based on weather conditions
- Improve classification accuracy

3. Lane Change Maneuver Inference (Inputs for Lane Change Maneuver Inference)

1) Environment context

Some research used more neighboring vehicles

ex) 6, 9 vehicles, consider vehicles within certain distance

Ideally consider more vehicles can improve the prediction performance

⇩ However

Surrounding vehicles are not always available due to sensor blockage or limitation

→ Large noise

→ Lead to false predictions

3. Lane Change Maneuver Inference (Inputs for Lane Change Maneuver Inference)

2) States of the Vehicle

Road coordinate system

- Longitudinal/lateral position, speed, acceleration
- Accurately represents vehicle position, direction, considering road features like lines and intersections
- Requires the road/marker information coming from the HD map, cameras, or other sensing devices

Track history

- lane change maneuver is regarded as a dynamic process
- Time series sent to algorithms such as Dynamic Bayesian Network, HMM, LSTM
- Requires sensing system having stable detection of the objects for a longer period of time

Turn signal

- Practical solution
- Also be used for other behavior, such as specific direction turning
- Improve its sensitivity

3. Lane Change Maneuver Inference (Inputs for Lane Change Maneuver Inference)

3) Driver Behavior

Eye and head movement → Detect driver's intention of the ego vehicle

Due to the sensor limitation

It is hard to use these signals to predict the surrounding vehicle's intention

⬇

With technological advancements

Brain waves, foot, hand, and gestures may be used for intention inference

3. Lane Change Maneuver Inference (Inputs for Lane Change Maneuver Inference)

4) Feature Selection

Sensing technologies keep being developed, number of available feature is also increasing

Selecting the most critical features as the inputs becomes an increasingly important topic

Feature[a]	Time to LC[b]	Effect Size[c]	Importance[d]
Lane Accessibility	0∼25(s)	$\boxed{0.78}$	-
Fro. Dis.	0∼2(s)	0.24	0.01
Fro. - Rel. Vel.	0∼2(s)	0.29	0.01
Adj. Fro. - Dis.	0∼25(s)	0.53	0.013
Adj. Fro. - Rel. Vel.	0∼25(s)	0.55	0.012
Adj. Rea. - Dis.	6∼25(s)	$\boxed{0.64}$	0.013
Adj. Rea. - Rel. Vel.	0∼20(s)	$\boxed{0.65}$	0.012
Tar. - Vel.	0∼10(s)	$\boxed{0.66}$	0.011
Tar. - Yaw Rate	0∼2(s)	0.2	-
Tar. - Indicator	0∼2(s)	$\boxed{0.78}$	-
Tar. - Lat. Pos.	0∼2(s)	0.32	-

Combination of features also plays an important role in improving predictive performance

Certain combinations should be avoided

3. Lane Change Maneuver Inference (Outputs of Lane Change Maneuver Inference)

Binary type

- Simplest and most widely used
- Lane changing or Not
- Provides less information

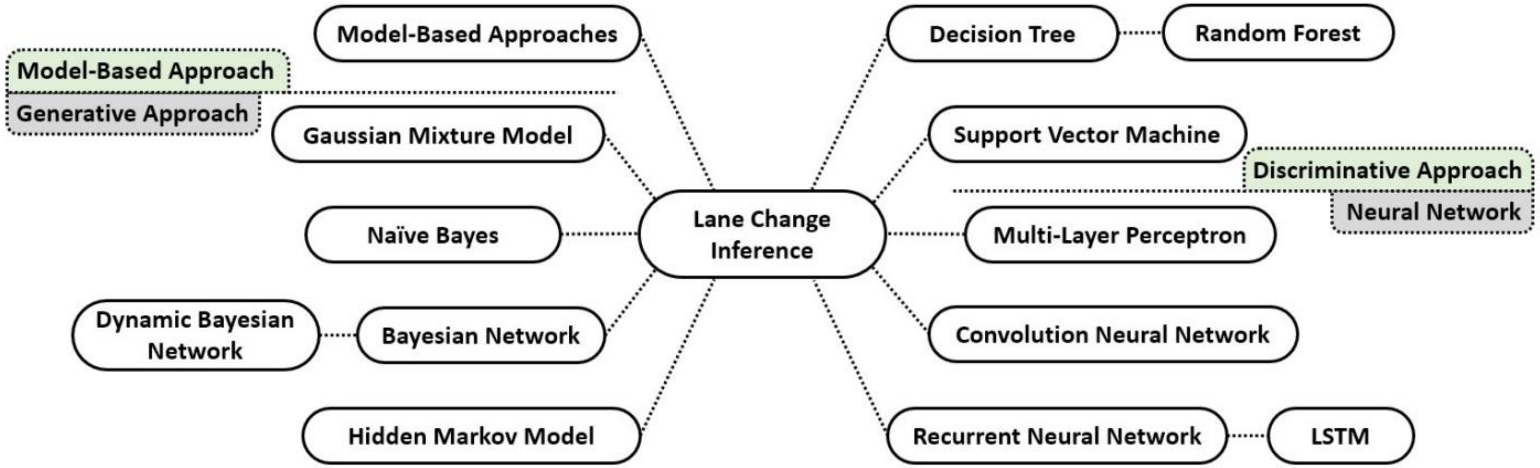
Probabilities

- Lane change and other maneuvers
- Providing specific probability values
- Controller react differently according to probability

Time to lane change

- Significant variable for controller to plan vehicle’s movement
- Not direct output of the lane change inference system
- How early inference system can identify a future lane change

3. Lane Change Maneuver Inference (Algorithms for Lane Change Maneuver Inference)



Model-based approaches

Machine learning approaches → Generative approaches, Discriminative approaches

Neural Network

3. Lane Change Maneuver Inference (Algorithms for Lane Change Maneuver Inference)

1) Model-based approaches

Driver behavior model

- Running multiple versions of behavior models in parallel
- lane change and lane following
- Compares each model's simulated behavior with actual observed behavior
- Infers the driver's most likely current intention

Driver decision-making process model

- Assumption that drivers are always choosing the maneuvers
  ↪ Best balance between safety and comfort
- How good a particular maneuver can be is usually formulated as a cost function
- Predicted maneuver will give the smallest cost

3. Lane Change Maneuver Inference (Algorithms for Lane Change Maneuver Inference)

1) Model-based approaches

Research

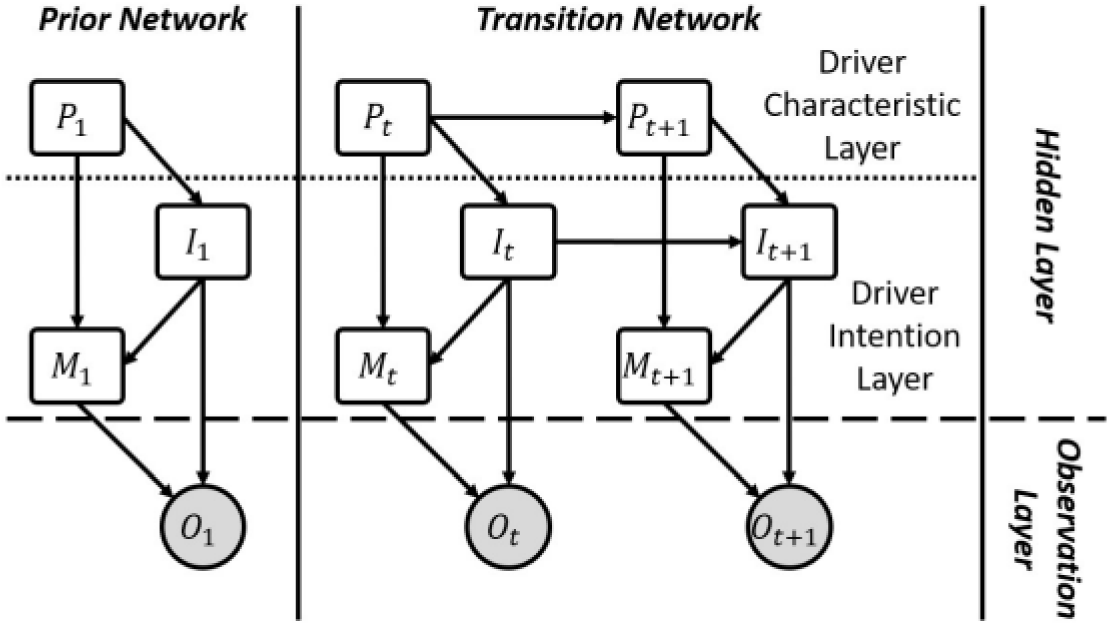
- Evaluating the collision probability of all the interacting vehicles
- Lead to exponential growth with the number of vehicles
- Only pairs of vehicles were considered instead of all vehicles at once
  ↪ Recursive way, Reduction in computational load

Results

- Generally good interpretability and provide long-term prediction
- Tuning of the cost functions or similarity metrics is usually challenging
- All vehicles will try to avoid collisions may not be true in some situation
- Drivers have different driving styles
  ↪ Lead to different behaviors

3. Lane Change Maneuver Inference (Algorithms for Lane Change Maneuver Inference)

2) Generative approaches



- Bayesian Network imitates human like-reasoning and decision making

- Bayesian Network computes and analyzes at each time step without using the history data

3. Lane Change Maneuver Inference (Algorithms for Lane Change Maneuver Inference)

3) Discriminative approaches
- Using SVM, Random Forest, Decision Tree

4) Neural Network
- Using RNN, LSTM, CNN

Algorithms	Strength	Weakness
Model-Based Approach	•Very good interpretability. •Usually requires less data than the other algorithms to build the model.	•Model is based on some assumptions that may not always be true. •There is usually no standard method for tuning.
Generative Approach	•Usually have good interpretability. •Most of the algorithms can provide probabilistic output.	•Need to model dependencies in the data.
Discriminative Approach	•Parameters are optimized for the classification problem, so usually have better classification performance.	•Usually can only output binary results •Poor interpretability.
Neural Network	•Due to its popularity, there are many methods and toolboxes available to use.	•Rely on large data set. •Interpretability is usually no good.

4. Validation and Evaluation

Paper	Main Sensors	Input Type	Algorithm	Output Type	Validation
[26]	-	vehicle status	LSTM	probability	NGSIM
[75]	-	vehicle status	Object-Oriented Bayesian Networks	probability	vehicle test
[28]	camera, Radar, Lidar	vehicle status	HMM	probability	vehicle test
[30]	camera, Radar, Lidar, Ultrasonic	vehicle status, traffic	Model with Bayeisan Classifier	probability, binary	vehicle test
[33]	laser scanner	vehicle status	SVM	binary	NGSIM
[24]	camera, Radar	vehicle status, road geomitry	Naïve Bayesian Gaussian Mixture	binary	vehciel test
[29]	-	vehicle status, environment	Bayesian Network	probability	Simulation
[98]	camera, Lidar	vehicle status, environment	HMM	binary	vehciel test
[62]	-	vehicle status, traffic, lane drop	SVM, Artificial Neural Networks (ANN)	binary	NGSIM
[25]	camera	vehicle status, environment	Random Forest	binary	vehciel test
[116]	-	vehicle status	MLP	probability	NGSIM
[52]	camera, Radar	vehicle status,	CNN	binary	vehciel test
[71]	-	vehicle status, environment	Dynamic Bayesian Network	binary	NGSIM
[53]	camera, Radar	vehicle status, traffic	Situation based Probability Estimation, SVM	probability	vehciel test
[63]	camera, Radar, Lidar, HD map	vehicle status, environment	Structural RNN	binary	vehciel test
[59]	-	vehicle status, traffic	HMM GMM	probability, binary	NGSIM
[14]	laser scanner, camera	vehicle status	Probabilistic Network	binary	vehciel test
[61]	-	vehicle status, traffic	Potential Field, SVM	binary	NGSIM
[72]	camera, Radar	vehicle status, traffic, road	Attention Network, LSTM	binary	NGSIM, vehicle test
[94]	-	vehicle status, traffic	Random Forest	binary	NGSIM
[130]	Radar and camera	vehicle status	HMM	probability binary	vehicle test
[131]	-	vehicle status,	Decision Tree	binary	SPMD
[132]	-	vehicle status, traffic	Multilayer Perceptron	binary	NGSIM
[133]	-	vehicle status, traffic	LSTM	binary	NGSIM
[109]	Radar and camera	vehicle status	Object-Oriented Bayesian Network	probability binary	vehicle test
[55]	V2V	vehicle status, road geomitry	SVM, Decision Trees, Random Forest	binary	vehicle test
[76]	-	vehicle status	Dynamic Bayesian Network	probability	highD
[134]	-		CNN, LSTM	binary	PREVENTION
[135]	camera, Radar	vehicle status,traffic	Gaussian Process Neural Networks	probability	vehicle test
[136]	-	vehicle status	LSTM	binary	highD
[73]	Radar, camera, map	vehicle status, traffic, road, weather	Random Forest, SVM, ANN, XGBoost	binary	SHRP2

highD
NGSIM

4. Validation and Evaluation

Accuracy

- Fraction of correctly classified maneuvers out of all predicted maneuvers
- Imbalanced test data set = lane keeping samples > lane change samples → misleading

F1-score

- Adjusting the threshold value

  ↪ Without modifying the other part of the inference system

T_{LC}

- Time to Lane Change
- tLC : Moment of the target vehicle performing the lane change maneuver
- tI : Time when first judges thaat the target vehicles would change lane

$$\tau_{LC} = t_{LC} - t_I$$

5. Conclusion

Lane change decision comes from the interaction between the driver and the environment

Using input features from different lane change stages can lead to different performance

6. How To Apply

Review of Other Studies Using Drone Data

Identifying Various Input Values That Can Be Utilized in Drone Data

Thank You

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